STAC67 Final Project Report

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[TO DO: make this in title page as required by rubric]

Research Context

[TO DO - yap about car price significance, what question we want to answer, how this can be beneficial knowledge for consumers/dealerships/car companies/manufacturers/etc.]

Exploratory Data Analysis

```
# read data file, published in 2024 on https://www.kaggle.com/datasets/mmakarovlab/serbia-car-sales-pri
car_price_data <- read.csv("serbia_car_sales_price_2024.csv")
```

Before we begin investigating, we notice that there are some issues with the data. Some rows are missing values under certain variables (i.e. #2, #233, #1705, etc.), and some variables are hard to work with. Knowing a car's **year** might be less informative than knowing its age, so we made a new column containing values for 2024 − Year called **age**. A car's **horsepower** is significant, but it's hard to use that data when it's given as two values in the format HP (kW), so we keep only the HP metric. Additionally, some variable names are hard to work with because of length or how it might interfere with R code, such as **car_mileage, km**, so we made those easier to process as well. As for the missing values, when we analyze the significance of a variable, we'll make sure to exclude rows where values for that variable are empty.

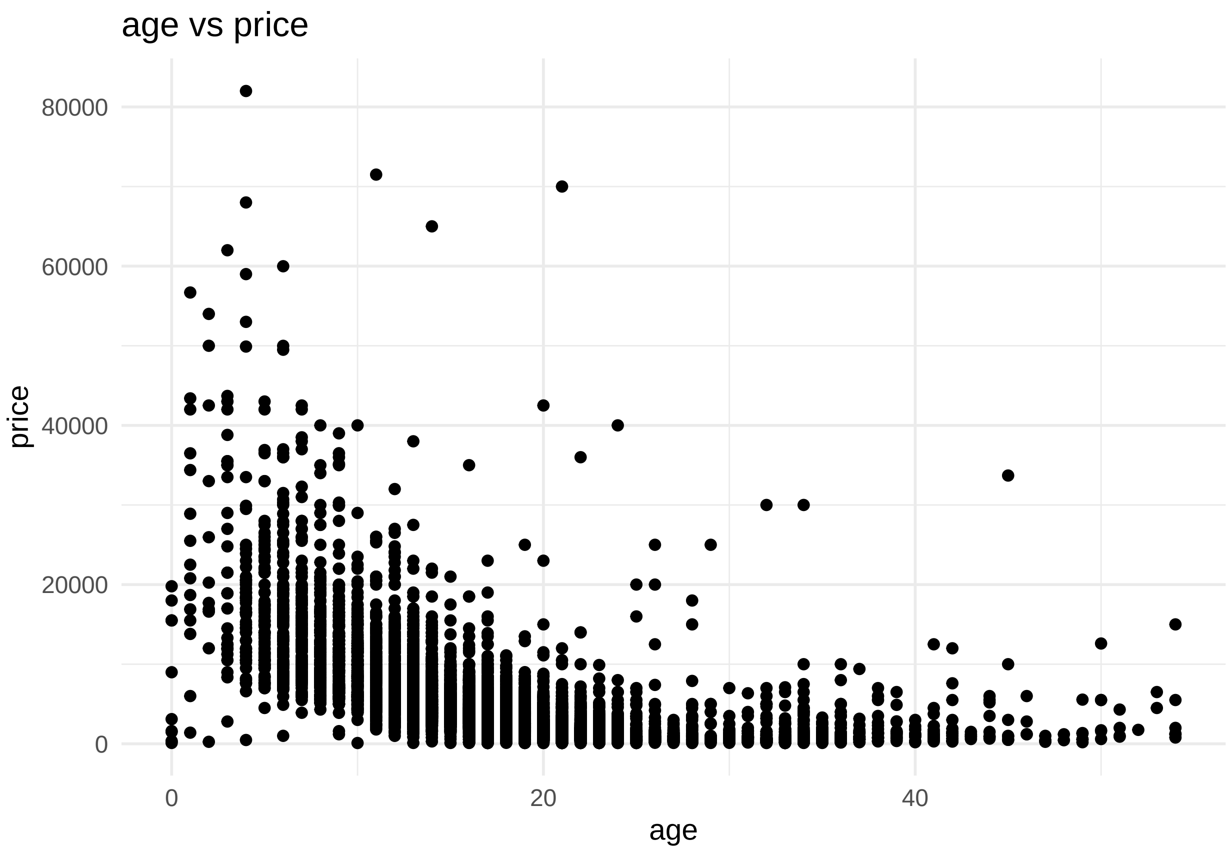
```
# data cleaning
car_price_data <- na.omit(car_price_data)
car_price_data$age <- 2024 - car_price_data$year # age is a continuous variable
car_price_data$horsepower <- gsub(pattern = "^(\\d+) HP.*", replacement = "\\1", car_price_data$horsepow

# making the variable names easier to process
names(car_price_data) <- gsub(pattern = "\\.\\..*", replacement = "", names(car_price_data))

summary(car_price_data)
```

```
##      views          favorite        post_info             price
##  Min.   :    0.0   Min.   :  0.000   Length:8403        Min.   :  100
##  1st Qu.:   61.0   1st Qu.:  0.000   Class :character   1st Qu.: 1600
##  Median :  114.0   Median :  1.000   Mode  :character   Median : 3300
##  Mean   :  307.9   Mean   :  2.665                      Mean   : 4844
##  3rd Qu.:  244.5   3rd Qu.:  3.000                      3rd Qu.: 5950
```

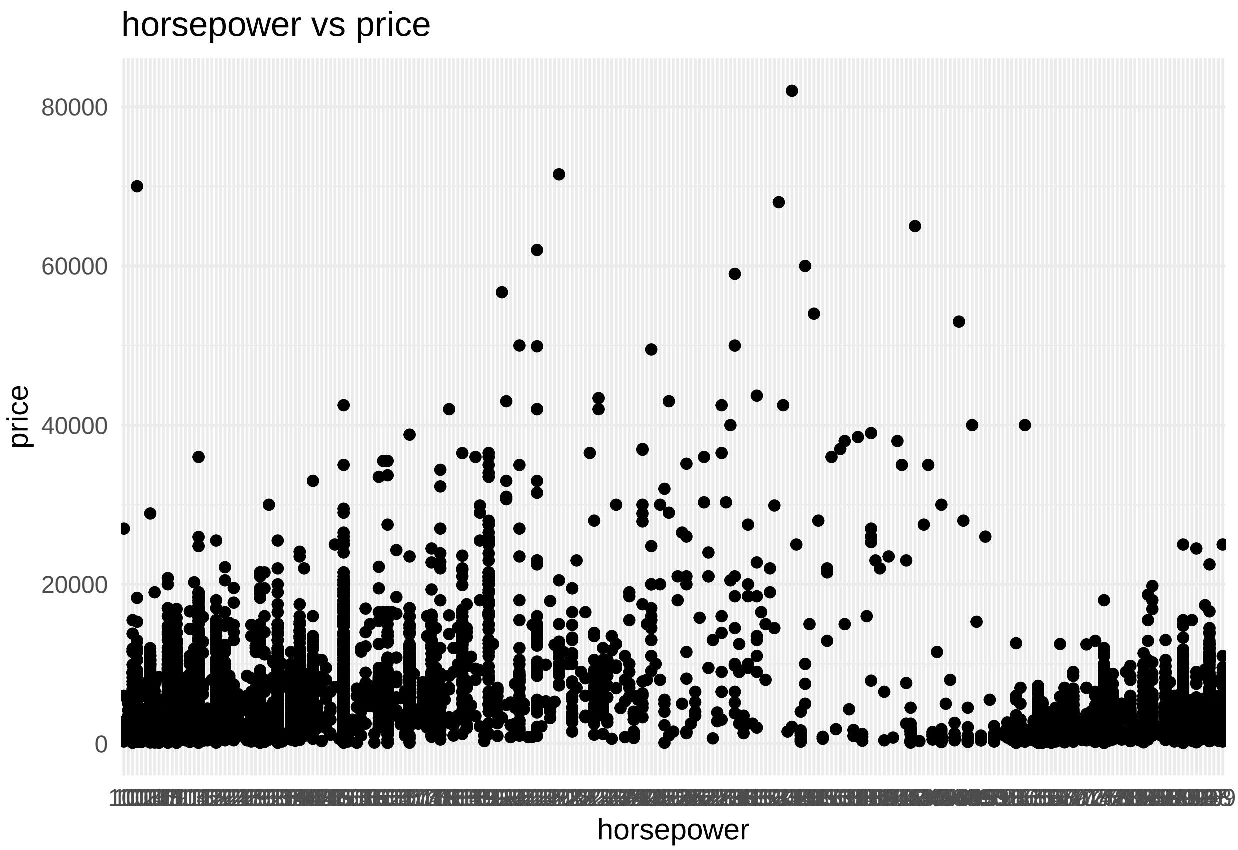
```
##  Max.   :27770.0   Max.   :151.000                      Max.   :82000
##    car_name              year          A.C            emission_class
##  Length:8403        Min.   :1970   Length:8403        Length:8403
##  Class :character   1st Qu.:2003   Class :character   Class :character
##  Mode  :character   Median :2006   Mode  :character   Mode  :character
##                     Mean   :2006
##                     3rd Qu.:2010
##                     Max.   :2024
##   seats_amount   horsepower           color            car_mileage
##  Min.   :2.00   Length:8403        Length:8403        Min.   :1.000e+00
##  1st Qu.:5.00   Class :character   Class :character   1st Qu.:1.767e+05
##  Median :5.00   Mode  :character   Mode  :character   Median :2.200e+05
##  Mean   :4.94                                         Mean   :2.852e+06
##  3rd Qu.:5.00                                         3rd Qu.:2.700e+05
##  Max.   :9.00                                         Max.   :4.295e+09
##  engine_capacity type_of_drive         doors               fuel
##  Min.   :  100   Length:8403        Length:8403        Length:8403
##  1st Qu.: 1400   Class :character   Class :character   Class :character
##  Median : 1700   Mode  :character   Mode  :character   Mode  :character
##  Mean   : 1725
##  3rd Qu.: 1995
##  Max.   :10000
##    car_type           gearbox               age
##  Length:8403        Length:8403        Min.   : 0.00
##  Class :character   Class :character   1st Qu.:14.00
##  Mode  :character   Mode  :character   Median :18.00
##                                        Mean   :17.86
##                                        3rd Qu.:21.00
##                                        Max.   :54.00
```

Now, we want to check on which variables are good predictors. For the continuous variables, we first plot scatter graphs for each variable against car price:

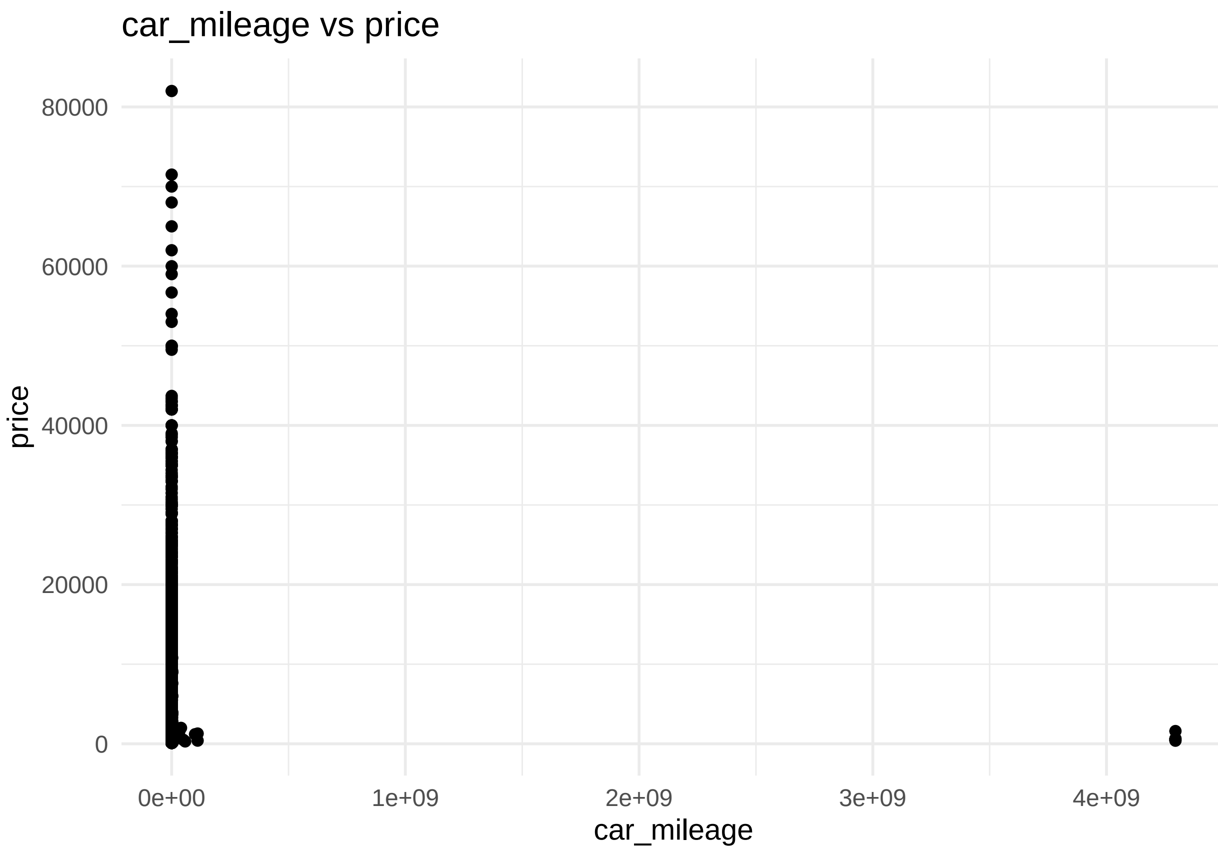
```
# TO DO: make this look nice. 2 or 4 scatter plots per line so it takes up less space
ggplot(car_price_data, aes(x = age, y = price)) + geom_point() + theme_minimal() + ggtitle("age vs pric
```



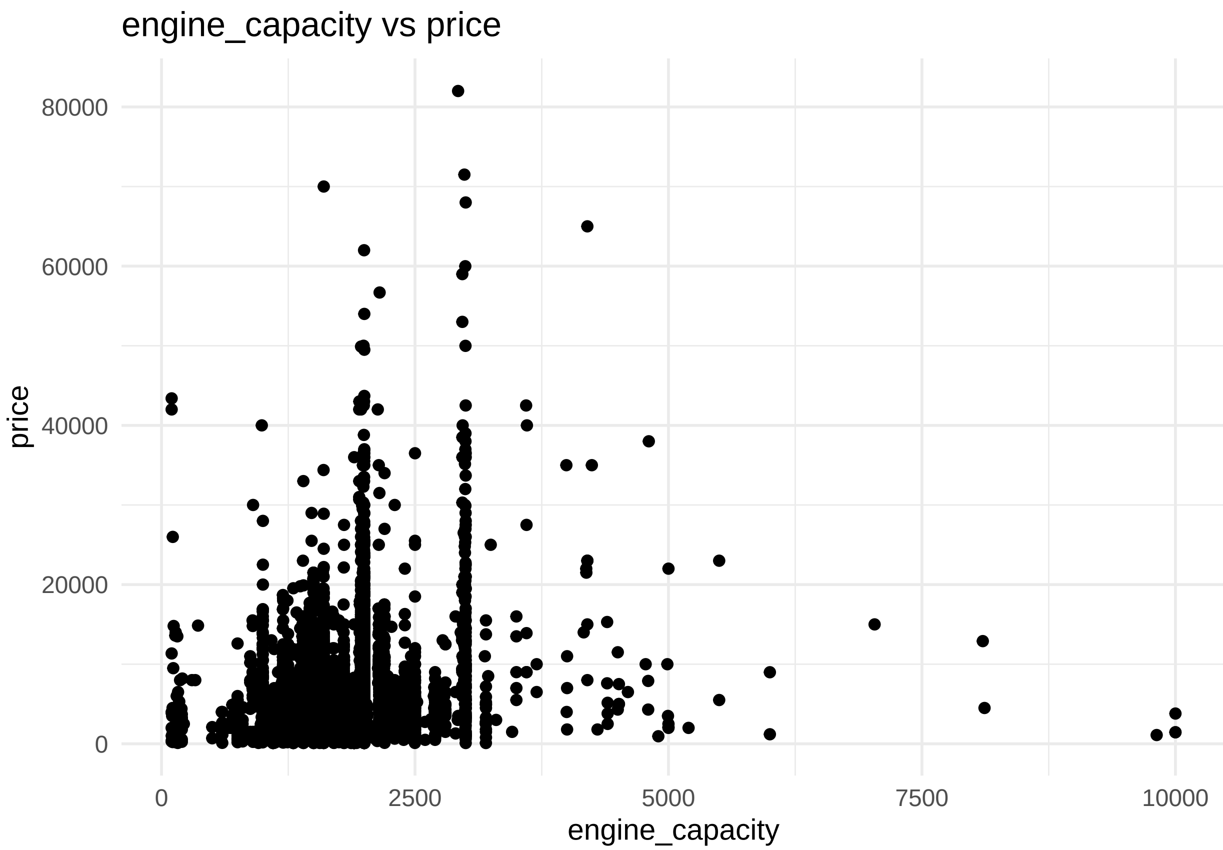

```
ggplot(car_price_data, aes(x = horsepower, y = price)) + geom_point() + theme_minimal() + ggtitle("hors
```




```
ggplot(car_price_data, aes(x = car_mileage, y = price)) + geom_point() + theme_minimal() + ggtitle("car_
```

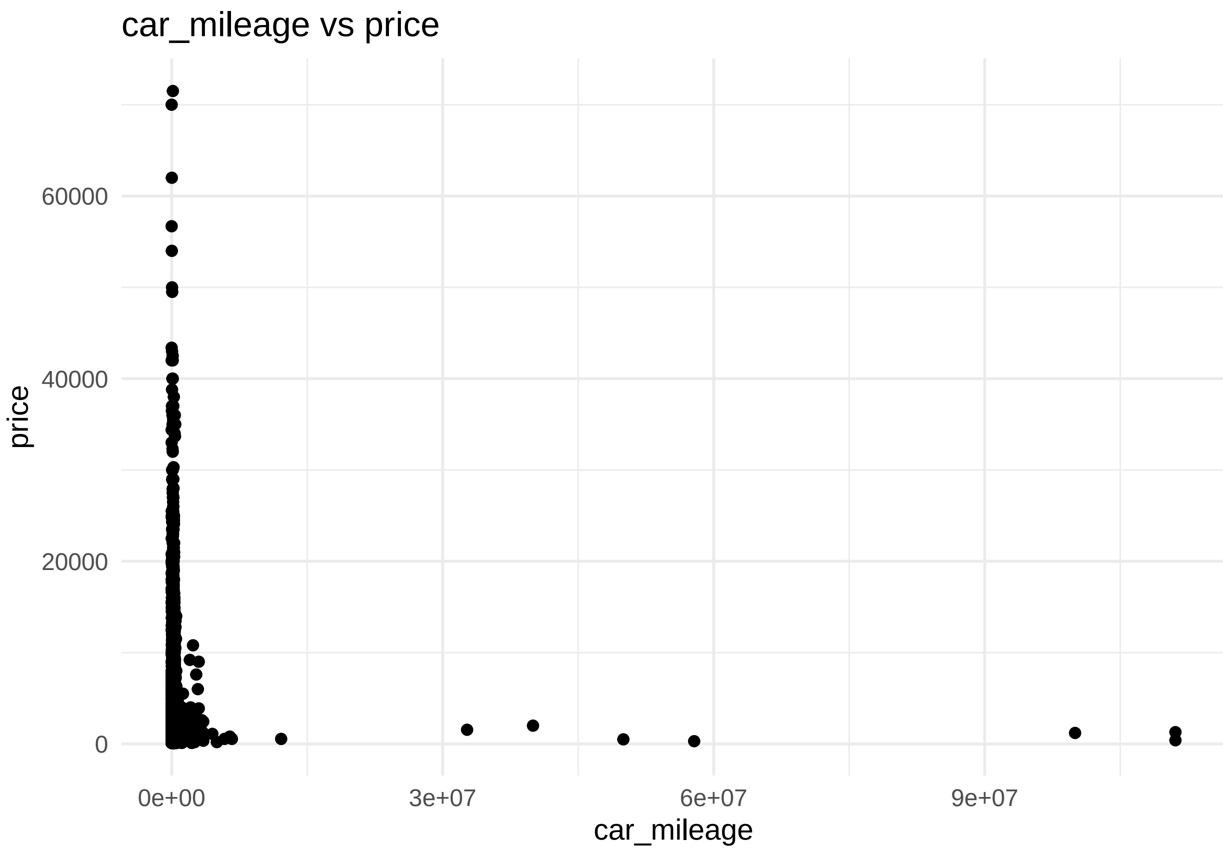



```
ggplot(car_price_data, aes(x = engine_capacity, y = price)) + geom_point() + theme_minimal() + ggtitle(
```



We notice that there are some influencial points (and possibly leverage points) on the car_mileage predictor. Let's get rid of those using hat values and semistudentized residuals to detect which ones are too high:

```
model <- lm(price ~ car_mileage, data = car_price_data)

# leverage points removal
leverage <- hatvalues(model)
threshold <- 2 * length(coef(model)) / nrow(car_price_data)
leverage_points <- which(leverage > threshold)
car_price_data <- car_price_data[-leverage_points, ]

# influential points removal
studentized_residuals <- rstudent(model)
outlier_indices <- which(abs(studentized_residuals) > 2)
car_price_data <- car_price_data[-outlier_indices, ]

ggplot(car_price_data, aes(x = car_mileage, y = price)) + geom_point() + theme_minimal() + ggtitle("car_
```




```
# TO DO: there is a bit of change here, it's better than before... but still pretty bad. If possible (a
```

Before we delve further into data analysis, we notice that there's some information in our dataset that is unlikely to be relevant, such as how many views or favourites the car posting gets, or the date of which it was posted. However, we need to run a t-test to make sure that those variables indeed do not have any influence on the final price of the car.

[TO DO: - get rid of certain variables like Views etc., justify using math/stats (can't just say "pretty sure it won't affect anything") - pretty sure it's just a basic beta_i = 0 t-test? correct me if I'm wrong]

[from here on is a load of garbage :(if you think you can help fix it, you're more than welcome. Though, it might be easier to just use this as code reference

-Rebecca]

Outlier Detection

[TO DO, pretty sure outliers are causing some of these other tests to look weird or become incomprehensible?]

Removing Leverage Points (outliers along X-axis):

Removing outliers along Y-axis:

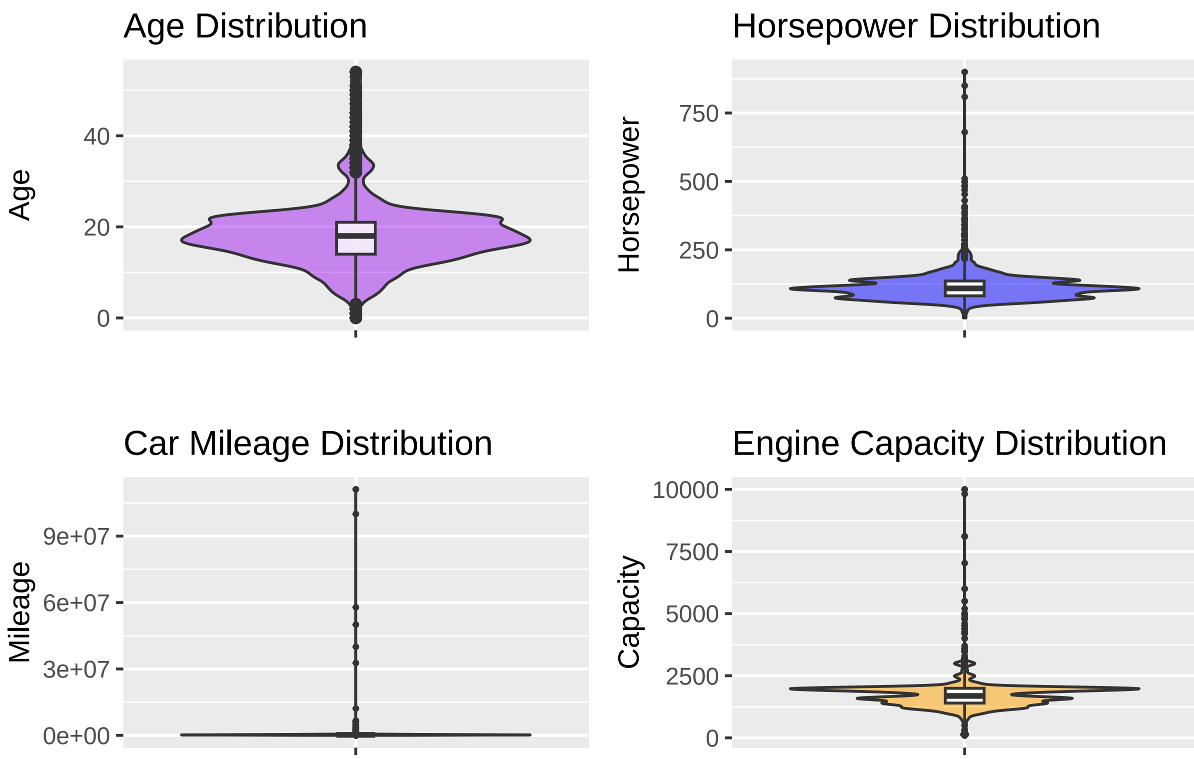
Removing Influential Points:

Data Analysis

[TO DO, need to analyse the variables by themselves - The violin plots are NOT what we want to see. Either they'll fix themselves after we remove outliers or we have to do something else]

Now, we want to take a look at the distributions of our data, to see if there are any peculiarities that we should be aware of. For continuous data: **age**, **horsepower**, **car mileage**, and **engine capacity**, we examine their violin plots:

```
library(ggplot2)
library(patchwork)

non_empty_age <- car_price_data[!is.na(car_price_data$age) & !is.na(car_price_data$age), ]

age_graph <- ggplot(non_empty_age, aes(x = "", y = age)) +
  geom_violin(fill = "purple", alpha = 0.5) +
  geom_boxplot(width = 0.1, alpha = 0.8) +
  labs(title = "Age Distribution", y = "Age", x = "")

non_empty_hp <- data.frame(horsepower = as.integer(car_price_data$horsepower[car_price_data$horsepower

horsepower_graph <- ggplot(non_empty_hp, aes(x = "", y = horsepower)) +
  geom_violin(fill = "blue", alpha = 0.5) +
  geom_boxplot(width = 0.1, fill = "white", outlier.size = 0.5) +
  labs(title = "Horsepower Distribution", y = "Horsepower", x = "")

non_empty_cm <- data.frame(car_mileage = as.integer(car_price_data$car_mileage[car_price_data$car_milea

# Plot for "car_mileage"
car_mileage_graph <- ggplot(car_price_data, aes(x = "", y = car_mileage)) +
  geom_violin(fill = "green", alpha = 0.5) +
  geom_boxplot(width = 0.1, fill = "white", outlier.size = 0.5) +
  labs(title = "Car Mileage Distribution", y = "Mileage", x = "")

non_empty_ec <- data.frame(engine_capacity = as.integer(car_price_data$engine_capacity[car_price_data$e

# Plot for "engine_capacity"
engine_capacity_graph <- ggplot(car_price_data, aes(x = "", y = engine_capacity)) +
  geom_violin(fill = "orange", alpha = 0.5) +
  geom_boxplot(width = 0.1, fill = "white", outlier.size = 0.5) +
  labs(title = "Engine Capacity Distribution", y = "Capacity", x = "")

all_plots <- age_graph + horsepower_graph + car_mileage_graph + engine_capacity_graph + plot_layout(nco
print(all_plots)
```

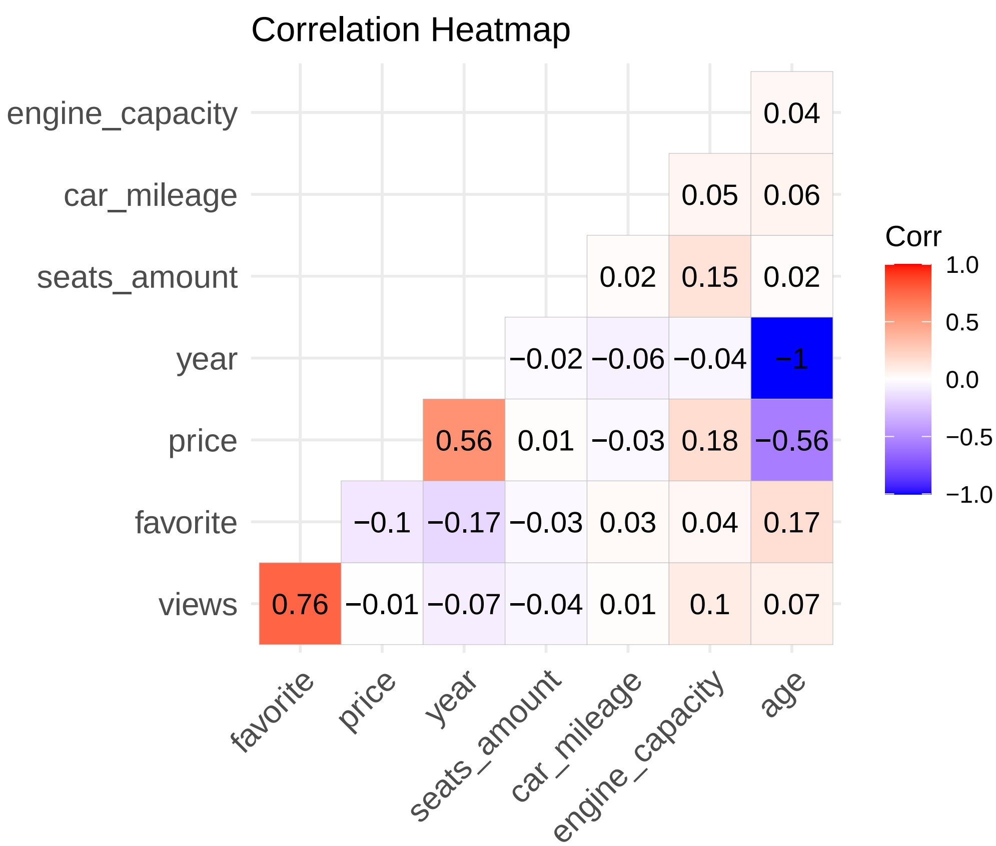


Correlation Analysis

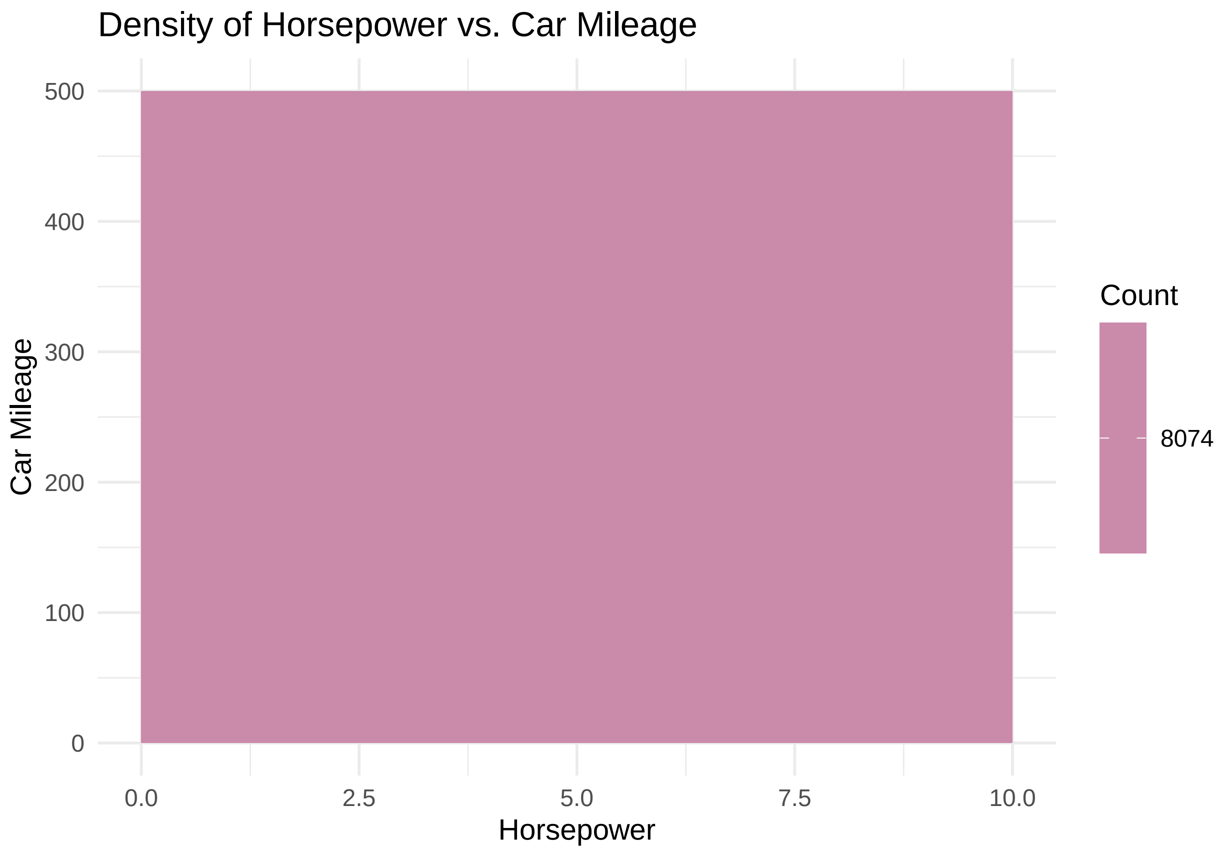
[Note from Rebecca (last person to work on this): this is a little broken right now.

- need to modify the correlation chart to get rid of some useless variables like views
- heatmap is not working I think bc there's a bunch of outliers in dataset. Going to clean out outliers first, then I'll get back to heatmap]

```r
library(ggcorrplot)

numeric_data <- car_price_data[sapply(car_price_data, is.numeric)]
cor_matrix <- cor(numeric_data, use = "complete.obs")

ggcorrplot(
  cor_matrix,
  method = "square",
  type = "lower",
  lab = TRUE,
  title = "Correlation Heatmap",
  colors = c("blue", "white", "red")
)
```




```r
car_price_data$log_horsepower <- log10(as.integer(car_price_data$horsepower))
car_price_data$log_car_mileage <- log10(as.integer(car_price_data$car_mileage))

ggplot(car_price_data, aes(x = log_horsepower, y = log_car_mileage)) +
  geom_bin2d(binwidth = c(10, 500)) +  # Adjust bin width for better visualization
  scale_fill_gradient(low = "blue", high = "yellow") +  # Density color scale
  labs(title = "Density of Horsepower vs. Car Mileage",
       x = "Horsepower", y = "Car Mileage", fill = "Count") +
  theme_minimal()
```


Density of Horsepower vs. Car Mileage
Car Mileage
500
400
300
200
100
0
0.0
2.5
5.0
7.5
10.0
Horsepower
Count
8074